https://doi.org/10.1590/jatm.v15.1312 REVIEW PAPER

Applications of Artificial Intelligence in the Air Transport Industry: A Bibliometric and Systematic Literature Review

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ABSTRACT

The use of artificial intelligence, along with its various components, is rapidly increasing in various fields of study today, going beyond the traditional domains of computer science and mathematics. To gain insights into how artificial intelligence is being applied in the air transport industry, uncover underlying correlations and trends in the literature, and identify potential research gaps, we conducted a systematic literature review supplemented with bibliometric elements such as keyword co-occurrence and author influence. The key findings of our research shed light on the most prolific institutions and authors globally involved in generating knowledge about AI applications in air transport. Additionally, we identified five research clusters that dominate the overall research direction: prediction and optimisation (constituting 65% of the articles), inter-industry collaborations (17% of the articles), human experience (9% of the articles), safety, risks, and ethical considerations (6% of the articles), and ecology and sustainable development (3% of the articles). Overall, further research is needed to explore the ethical implications, legal considerations, integration processes, and impact on employment and the environment in the air transport industry.

Keywords: Artificial Intelligence; Air Transport; Big Data Technologies; Air Traffic Management: Airlines; Airports.

INTRODUCTION

The usage of analytical and numerical methods has pervaded two main fields today, business and research. In the former, these methods are increasingly used to improve and enhance returns, which could take the form of financial gains or simply optimised operations efficiency (Delen and Ram 2018). While in research, the rapidly growing usage of analytical methods could be assimilated to a reflection of scientific progress (Mazanec *et al.* 2010). In the current advanced technological era, the usage of analytical, statistical, and other scientific methods is given an even greater depth by the introduction of "intelligent" elements, commonly defined under the non-expert term of Artificial Intelligence (AI). In many areas today, AI and its subfields are constantly reshaping and challenging our view of what can be accomplished (Allam and Dhunny 2019).

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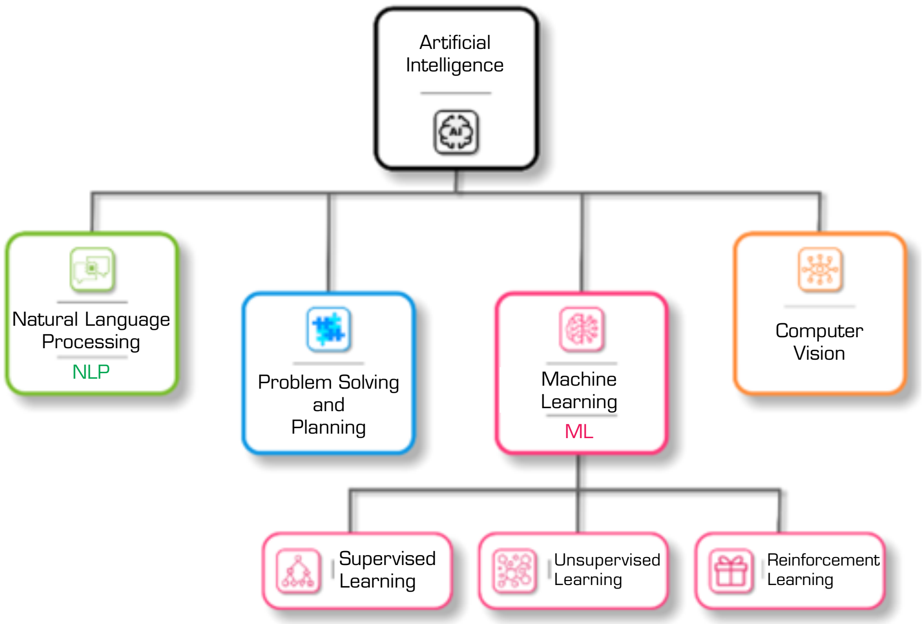
As any other field, air transport relies heavily on different quantitative and qualitative analysis methods in order to provide adequate insight for researchers and practitioners alike. In today's inextricably connected world, where the use of Artificial Intelligence is surging in every industry, in addition to the insight provided by previous literature reviews, there is an actual demand for finding, studying and explaining the links tying AI and air transport. This work aims at filling this gap by studying available literature and identifying the various applications of AI in air transport.

Artificial intelligence

Artificial Intelligence, despite its widespread use, remains a complex concept that defies a simple definition. Scholars like Hamet and Tremblay (2017) and Kaplan and Haenlein (2019) offer a synthesised generalisation, defining AI as a collection of algorithms designed to mimic human intelligence to some extent. These algorithms can interpret, analyse, and propose actions based on provided data without explicit programming. AI encompasses various subfields, each with distinct applications. Notably as shown in Fig. 1, Machine Learning, Computer Vision, and Natural Language Processing (NLP) stand out as some of the most well-known AI applications.

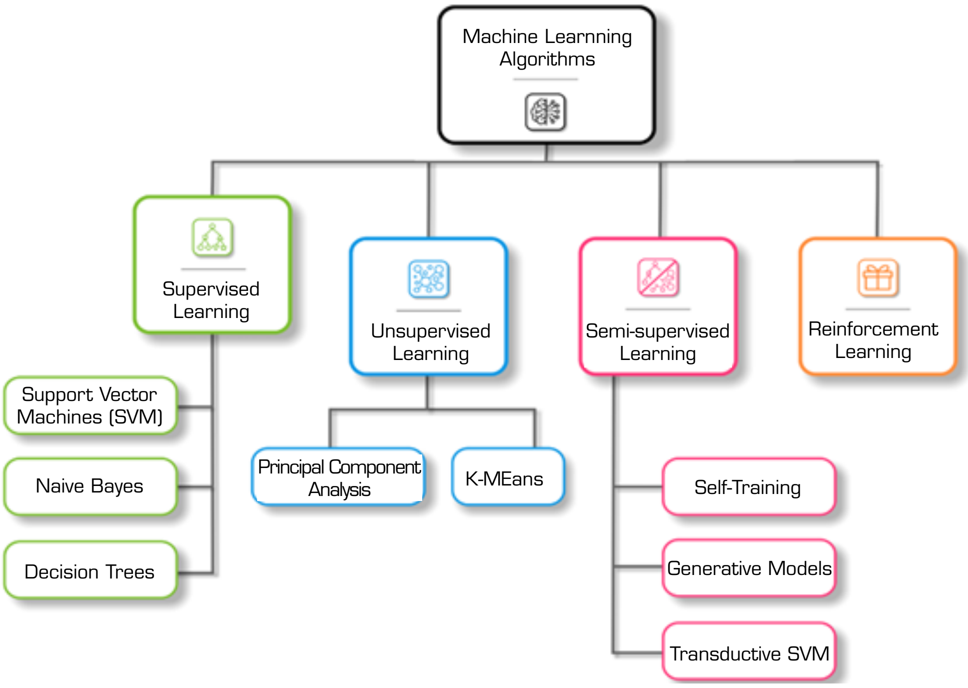
These applications find relevance across various domains, spanning fields like medicine, surveillance, transportation, pricing, operations, military applications, and intelligent enterprise planning (Smith and Eckroth 2017). In numerous studies, the term "AI" is closely associated with other terms such as "Big Data Technologies (BDT)", "Machine Learning (ML)", or "Intelligent Analytics" (Kibria *et al.* 2018). While there may be disagreement among scholars regarding the precise terminology of these concepts, a consensus exists that data serves as the common currency connecting them all (Kersting and Meyer 2018).



Source: Adapted from Antoniou *et al.* (2011).

Figure 1. A summarised view of the various concepts contained within Artificial Intelligence.

The algorithms used to develop intelligent systems widely vary in terms of complexity, suitability, and area of application. Even though most of these algorithms fall under the auspices of Machine Learning, they are still a contributing sub-component of AI as a whole (Helm *et al.* 2020). With the variety of problems encountered today, it is safe to assume that there is no one-size-fits-all solution. With that perspective, ML algorithms are usually categorised into 3 main paradigms: supervised, unsupervised, and reinforcement learning. The desired outcome and the type of available data, control the category of the techniques that can be employed (Ray 2019). Figure 2 illustrates a glimpse of these various ML techniques.



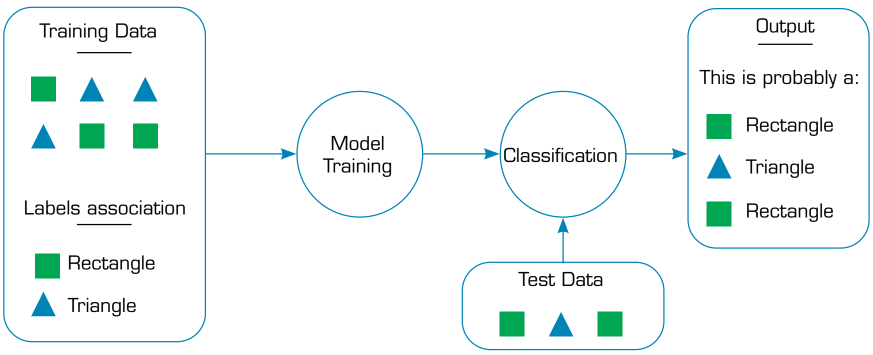
Source: Adapted from Mahesh (2020).

Figure 2. Most prominent machine learning algorithms and their subcategories.

As these multiple ML approaches constitute a research area mainly pursued in the fields of computer science and engineering, they will only be briefly introduced in the following subsections to provide the reader with the notions required to understand the practical applications of AI in the air transport industry.

Supervised learning algorithms

Supervised machine learning refers to the case in which an agent (an algorithm) performs an input-output matching of the data, based on various patterns observed in the training sets (or examples) of input-outputs (Praveena and Jaiganesh 2017). Supervised learning algorithms earned this denomination as a result of always requiring an external intervention, because detecting and arranging such patterns necessitates labelling historic data for it to be readily used for the training phase (Mahesh 2020). Support Vector Machines (SVM), Bayesian models, and decision trees are some of the most well-known algorithms used in this type of learning. Figure 3 shows an abstract example of the general functioning of a supervised machine learning algorithm, trained and used for shape classification.



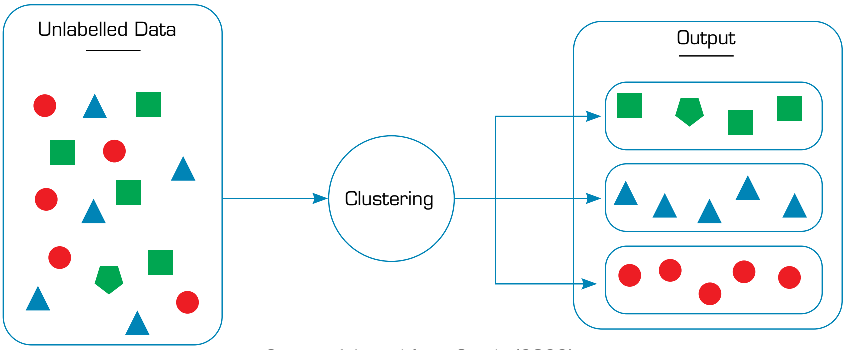
Source: Adapted from Oracle (2022).

Figure 3. Process of training and testing a supervised agent to classify shapes.

Unsupervised learning algorithms

Unsupervised machine learning, also known as "cluster analysis", "class discovery" or "outlier detection", is significantly different from supervised learning. More specifically, this type of algorithm does not require data labelling. In simple terms, this means that there is no right answer for the algorithm to find, rather it must categorise features and try to find motifs on its own, implying no external intervention. This independence from external influence has given the epithet of "unsupervised" to these types of systems (Gentleman and Carey 2008; Mahesh 2020). Some of the algorithms that fall under this category of learning include for example: Principal Component Analysis (PCA) or K-means clustering.

The use of unsupervised data processing can lead to anomalies or errors in the output clusters, as certain data points may be assigned to a cluster that does not correspond to their true nature (Liang and Klein 2008). This is demonstrated in the example of shape clustering shown in Fig. 4, where the agent successfully identifies three classes of shapes, but incorrectly assigns a pentagon to the cluster of rectangles.



Source: Adapted from Oracle (2022).

Figure 4. Example of a shape clustering unsupervised algorithm.

Semi-supervised learning algorithms

Semi-supervised learning is an in-between path that allows an escape from the binary categorisation of problems. Many approaches in the domain of semi-supervised learning involve the extension of either unsupervised or supervised learning methodologies to incorporate supplementary information commonly associated with the alternate learning paradigm (Hady and Schwenker 2013).

In the case of "semi-supervised classification", the agent is trained from both the labelled and unlabelled data, which is better than the supervised classifier trained on the labelled data alone. While in "constrained clustering", the goal is to obtain better clustering than the clustering from unlabelled data alone (Zhu and Goldberg 2009).

Semi-supervised learning is useful when the access to labelled data is limited or expensive. This approach however faces many challenges in real-world applications, as some empirical studies (Blum and Chawla 2001; Chen and Wang 2010; Nigam *et al.* 2000) show that there are cases in which the use of the unlabelled data may degenerate the performance. Zhu and Goldberg (2009), further argue that semi-supervised learning performance depends on the correctness of the assumptions made by the model.

Reinforcement learning algorithms

All the previously discussed algorithms share a common goal: finding correlations and patterns in large data sets. Reinforcement learning algorithms are different, as they are firmly oriented towards maximising cumulative rewards (Mahesh 2020; Oh *et al.* 2020).

Under this paradigm, the primary objective of the agent is to effectively maximise the received reward signal within the given environment. However, at the start of its interaction with the environment, the agent is initialised devoid of any prior knowledge or experience. Consequently, the agent must embark on an exploratory phase to navigate through the state space and determine the most favourable actions (Sutton and Barto 2018).

The agent faces the intricate task of navigating the trade-off between exploration and exploitation to maximise rewards in a dynamic and uncertain environment. This delicate balance is further influenced by factors such as stochasticity, delayed rewards, and non-stationarity, making exploration a vital component for the agent's ongoing optimal decision-making process (Nian *et al.* 2020).

Despite being one of the 3 main machine learning paradigms, reinforcement learning remains difficult to implement, for the simple reason that the notion of "reward" can be difficult to determine and may vary from one application to another (Oh *et al.* 2020).

Special case of Artificial Neural Networks

In an effort to mimic the neurons and neural networks in the human brain, Artificial Neural Networks (ANN) have been and continue to be developed for effective problem resolution using complex data sets (Silva *et al.* 2017). ANNs have been set as a special case because they can be used to solve problems from any category (supervised, unsupervised, and reinforcement). The usual structure of an ANN consists of an input layer, a hidden layer, and an output layer. A neural network is referred to as 'shallow' when the hidden layer consists of a single array of neurons, while a network with multiple layers is called 'deep' (Bianchini and Scarselli 2014; Lopez-Martin *et al.* 2019). Generally, the hidden layer(s) process(es) the input data through weighted calculations, and the results are then conveyed through the output layer (Mahesh 2020).

AI and Air Transport

The application of artificial intelligence in the air transport industry has become increasingly prevalent, offering improvements in safety, efficiency, and customer service. Across various aspects of air transport, a multitude of analytical methods are employed to support the industry in various ways. These methods enable the industry to better predict flight demand, optimise schedules and pricing, analyse aircraft data to predict maintenance needs, optimise slot distribution for landing aircraft, facilitate air traffic management, plan fuel-efficient routes, and enhance the passenger experience through AI-powered chatbots and virtual assistants. By incorporating AI into these areas, significant advancements in efficiency and quality can be achieved, leading to better outcomes for the industry as a whole.

When examining the applications of AI in various industries, it is common to find reviews that group together the subfields of a particular industry and discuss them collectively. However, in the case of air transport, it is justified to specifically research the applications of AI in this domain. Unlike other transport subfields, air transport is a vast and distinct field that warrants individual attention. Moreover, the abundance of AI applications in air transport shows great promise and is supported by high-quality studies. For example, Nikitas *et al.* (2020) explore the intersection of AI, transport, and smart cities, focusing on autonomous vehicles and Unmanned Aerial Vehicles (UAVs). Another comprehensive review by Abduljabbar *et al.* (2019) delves into various AI algorithms used to enhance different aspects of the aviation industry, including congestion relief, landing safety, and in-flight monitoring systems, among others. These reviews suggest that while algorithmic and optimisation interventions receive significant research attention, other applications like UAVs are still in their early stages and require further development over time.

The background section of this work offers definitions and explanations to enhance understanding of the topic. It is followed by a methodology section that outlines the step-by-step process undertaken to obtain the results presented in this study. Subsequently, the bibliometric and network analyses of these results are presented in separate sections, followed by a discussion of the findings. Finally, the concluding section provides recommendations for future research in this field and addresses the limitations encountered during the study.

METHODOLOGY

The methodology of a literature review becomes particularly relevant when the objective of the research is to explore existing studies and identify potential avenues for investigation. A literature review serves to consolidate previous research conducted in related fields, providing a comprehensive overview of prior thoughts and actions regarding the addressed problem (Boell and Cecez-Kecmanovic 2014). Within the realm of literature analysis, a systematic literature review (SLR) goes a step further in terms of depth and rigor compared to narrative reviews. SLRs follow a rigorous and auditable process, distinguishing them from descriptive narrative reviews that often focus on a subset of selected studies within a specific area (Bhandal *et al.* 2022). Systematic reviews offer a reliable and replicable approach, allowing the synthesis of a robust knowledge base from a wide range of literature sources. This method aims to minimise bias by analysing all relevant studies on the topic, regardless of the authors or their primary field of expertise (Uman 2011). Given the nature and objective of our research, we have adopted a systematic literature review approach, supplemented by elements of bibliometric analysis.

Keywords definition

The first step in the adopted methodology consists of selecting the appropriate keywords that will be used to browse the Scopus database. Keyword choice was already clear as our research focuses on the applications of AI in the air transport industry.

Although the terms AI, ML, and Big Data are usually based on a recurring set of tools, they are not equivalent to one another. Additionally, two separate contexts were set to classify chosen keywords for higher clarity, an "industry" context and a "tools" context. The Boolean operator "OR" is used to link keywords, while the "AND" operator is used to link contexts.

Industry context keywords include: "air transport", "aviation", "airline", "airport", "air traffic management".

While tools context keywords are as follows: "artificial intelligence", "machine learning", "big data".

The next step involves entering the chosen search terms into the search engine of a selected database and retrieving the results. Scopus has been selected as the preferred database due to its encompassing features, which make it comparable to other similar systems like PubMed and Web of Science. In terms of article availability and the range of search parameters it offers, Scopus is considered comprehensive and robust (Falagas *et al.* 2008). It provides both basic and advanced search options, allowing for the application of various filters to refine the search results, including publication type, publication date, Scopus addition date, subject area, and author name.

Search results

The initial search was conducted on July 20, 2022, using the specified query in the Scopus database search engine. This search yielded a total of 4,220 documents. Subsequent filtering steps were applied, as outlined in Table 1, to refine the results. The filters included selecting English-only publications, peer-reviewed articles, and limiting the publication date to the last five years, resulting in 1,067 articles. Additionally, the option to display only open-access articles was enabled to ensure unrestricted access to the full texts.

Table 1. Summary of articles collection, filtering, and screening strategy.

Step	Action	Output quantity
1. Input selected search terms	Tools context: ("artificial intelligence" OR "machine learning" OR "big data ") AND Industry context: ("air transport" OR "aviation" OR "airline" OR "air navigation" OR "airport" OR "air traffic management")	4220 documents
2. Filtering	Limit query to English only documents Limit document type to articles Limit publication year to last 5 years (2017-2022)	1067 articles
3. Screening	Full access only Screen the abstracts and keywords for relevance	216 articles
4. Final selection	Check for doubles	216 articles

Source: Elaborated by the authors.

During the screening phase, abstracts and keywords were carefully examined for relevance to this study. Some studies that were unrelated, primarily those focused on medical research but included keywords such as "aviation" or "airline" for illustrative purposes, were identified and excluded. Furthermore, studies that solely aimed to solve mathematical problems and used "airports" or "airlines" as examples were also discarded based on their end purpose.

The final sample of 216 articles underwent a thorough review to identify any duplicates, and none were found.

BIBLIOMETRIC ANALYSIS

The bibliometric analysis conducted in this section plays a crucial role in comprehending the different trends that shape the literature on AI and air transport. To begin with, the analysis includes influence statistics that identify and rank the most impactful researchers and institutions from various geographical regions. The visualisations of bibliometric data presented in this study were generated using VOSviewer, a software tool designed for constructing and visualising bibliometric networks based on citation, co-citation, coupling, or co-authorship relationships. While VOSviewer offers a range of valuable features and is freely available for use, its source code is not accessible for sharing or redistributing. However, it is worth noting that a new web-based version of the software is currently being developed and is expected to be open-source (Van Eck and Waltman 2010).

The developers of this software have introduced a novel algorithm that effectively clusters the literature by grouping related nodes into distinct clusters. The number of clusters generated depends on the optimal solution of the optimisation problem presented in Eq. 1 (VOSviewer clustering optimisation problem) (Waltman and Van Eck 2013).

$$V(c_1, \dots, c_n) = \sum_{i<j} \delta(c_i, c_j)(s_{ij} - \gamma) \tag{1}$$

Where: c_i denotes the cluster to which node i is assigned; $\delta(c_i, c_j)$ is a function that equals 1 if $c_i = c_j$ and 0 otherwise; S_{ij} represents the similarity factor between nodes i and j; γ denotes a clustering resolution parameter. The higher the value of γ, the larger the number of clusters that will be obtained.

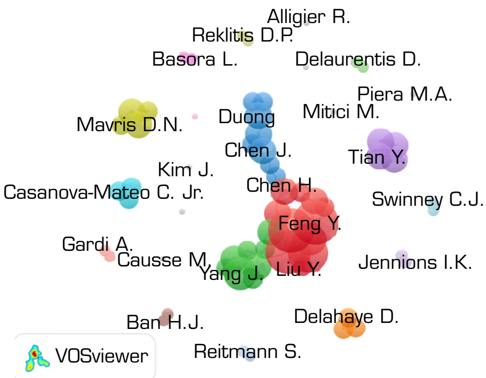
The algorithm used by VOSviewer and the ones used by other famous bibliometric visualisation tools are surprisingly similar. Gephi for example, uses the Louvain algorithm as a literature clustering approach, which is a model that aims to determine the optimal number of partitions that maximise the modularity index through multiple iterations (Blondel *et al.* 2008). VOSviewer, on the other hand, uses the smart local moving algorithm, which employs a recursive method to identify the structure of the bibliographic network and its elements (Waltman and Van Eck 2013).

Using the Scopus export option, a comma-separated-values format (CSV) file was generated containing the filtered search results. This file was edited to remove any non-selected studies, and was then used as an input to VOSviewer.

Author influence

By employing VOSviewer's co-authorship analysis method, we conducted an analysis on 216 selected studies to identify the frequency of recurring authors and the strength of their collaborations. The results were visualised in Fig. 5, revealing the presence of 16 visible clusters of authors out of a total of 23 clusters. The largest cluster comprises the most influential authors who have established numerous strong connections. Although the number of collaborations may be limited, this indicates a genuine endeavour among researchers to advance the field of AI applications in air transport and expand the boundaries of knowledge in this area.

Mavris D N, Puranik, T G and Li J emerge as the most productive authors in this research field, each having contributed in 5 articles. It is worth mentioning that although Mavris is a prolific author, their influence cluster appears to be limited, suggesting a relatively lower level of collaboration compared to other authors.



Source: Elaborated by the authors.

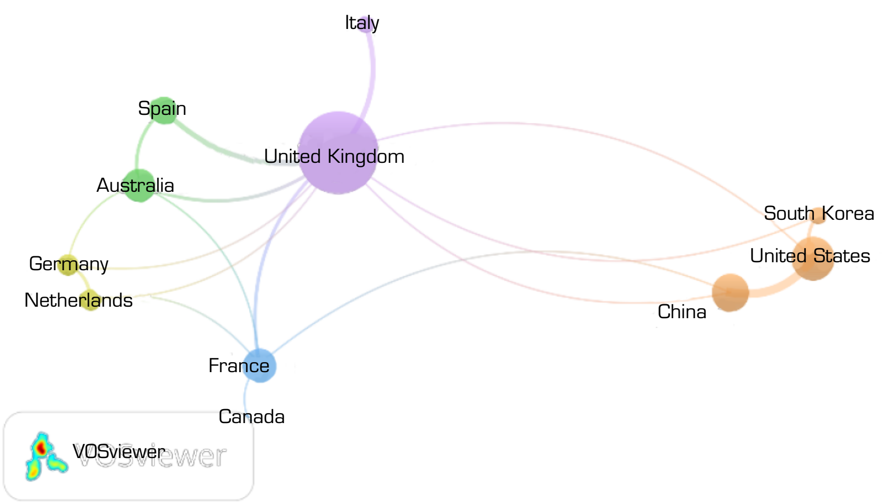
Figure 5. Author co-authorship map with article production bar graph for top authors.

Geographical influence (institutions or cities)

The affiliations field, an essential component when exporting search results from the Scopus database, provides valuable information about the primary institutions associated with each study, including their city and country. This field proves to be particularly valuable for analysing the geographical impact within the field of AI and air transport. By exporting this data, we can identify and quantify the top contributing institutions based on the number of published papers they have produced.

In terms of geographical distribution, the publication of studies on AI applications in air transport showcases the global interest and engagement of various institutions. Figure 6 highlights the top 11 territories based on study production, revealing that China and the United States of America are the primary contributors, surpassing other territories in terms of the quantity of studies.

Furthermore, there is a strong collaboration link between these two countries. However, the United Kingdom stands out with the highest total link strength, indicating a robust network of collaborations extending to numerous territories.



Source: Elaborated by the authors.

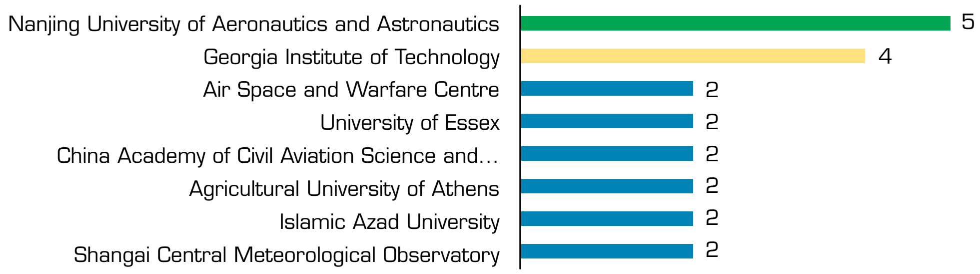
Figure 6. Article production and link map by territory with publications bar graph.

Furthermore, we conducted an examination of the global research trend by visualising the affiliations fields using the free Google MyMaps tool. The resulting map, depicted in Fig. 7, provides insights into the distribution of contributing institutions. Consistent with our previous analysis, the density of institutions appears to be higher in the European continent, particularly in regions such as the UK, Germany, and the Netherlands. Additionally, two other notable clusters can be observed in the Chinese region of Asia and in the United States in North America. In contrast, Canada, Russia, Australia and countries in South America and Africa show comparatively lower research output in this field.

Source: Elaborated by the authors.

Figure 7. World-map with geographical location of contributing institutions.

Additionally, the analysis of institutional contributions, depicted in Fig. 8, reveals that China and the UK are the leading countries with the highest number of institutions actively involved in research on AI applications in aviation. This finding reinforces the previous observation that there is a significant interest and investment in this field of study across multiple regions, particularly in the Eurasian region of the world.



Source: Elaborated by the authors.

Figure 8. Article production by top institutions bar graph.

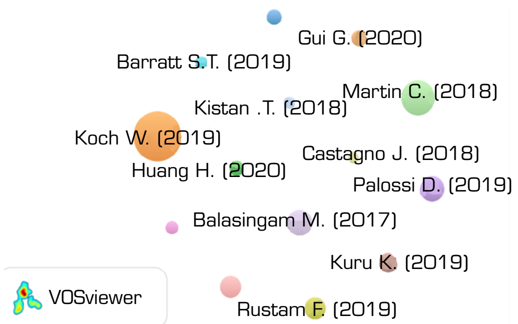
NETWORK ANALYSIS

VOSviewer, a powerful software tool, facilitates network analysis by allowing the visualisation of large networks through multidimensional scaling. This capability proves invaluable during the process of exploring literature (Van Eck and Waltman 2010; VOSviewer 2022). Moreover, this software provides valuable insights into the overall structure of the AI applications in the field of air transport, thanks to features such as modularity-based clustering analysis (Huang *et al.* 2022; Newman and Girvan 2004). Our network analysis comprises two main components: citation analysis and keywords co-occurrence analysis.

Citation analysis

Citation analysis is a bibliometric technique employed to assess the impact and prominence of a publication. This method examines the frequency with which a publication is cited in other works to gauge its reputation and influence (Ding and Cronin 2011). By tracking the references cited in different articles, citation analysis provides valuable insights into the scholarly communication patterns within a specific field (Hoffmann and Doucette 2012).

Conducting a citation analysis with VOSviewer is a simple process that involves utilising the generated CSV file from our sample of 216 selected studies. In Fig. 9, the top 36 articles are represented in a constellation, where the size of each node corresponds to the number of citations received by the respective study. The most frequently cited article, authored by Koch *et al.* (2019) and focusing on Reinforcement learning for UAV attitude control, stands out with 127 citations.



Source: Elaborated by the authors.

Figure 9. Most cited articles map with top cited authors bar graph.

Keywords co-occurrence analysis

Keywords play a crucial role in providing a concise yet informative description of research content (Rajagopal *et al.* 2017). By analysing the co-occurrence of keywords, researchers can identify clusters, uncover underlying patterns, and determine thematic relationships. This approach is based on the assumption that the connections between keywords reflect the knowledge structure of the scientific or technical field under investigation (Radhakrishnan *et al.* 2017; Stegmann and Grohmann 2003).

In our sample of 216 papers, we identified a total of 2,145 keywords. By applying a minimum threshold of 10 occurrences for each keyword, we obtained a refined list of 29 keywords (refer to Table 2). It is not surprising that "machine learning" emerged as the top-ranking term, with a frequency of 105 and a link strength of 355. From a search perspective, this indicates that "machine learning" is the most prominent keyword used to explore literature in this particular field of study. Other frequently occurring keywords include "air transportation" (frequency = 41, link strength = 199), "learning systems" (frequency = 39, link strength = 204), and "artificial intelligence" (frequency = 39, link strength = 118), which align with the subject matter being investigated.

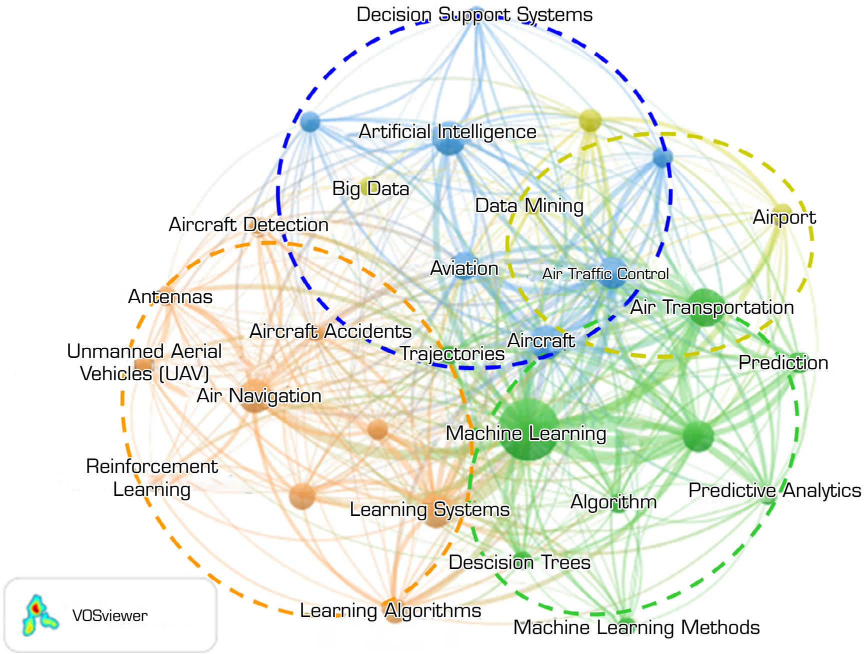
Table 2. List of top 29 most frequent keywords.

Keyword	Freq.	Keyword	Freq.	Keyword	Freq.
Air Navigation	38	Artificial Intelligence	39	Learning Systems	39
Air Traffic Control	34	Aviation	28	Machine Learning	105
Air Traffic Management	16	Big Data	13	Machine Learning Methods	10
Air Transportation	41	Data Mining	11	Neural Networks	16
Aircraft	38	Decision Making	16	Prediction	17
Aircraft Accidents	11	Decision Support Systems	11	Predictive Analytics	13
Aircraft Detection	15	Decision Trees	14	Reinforcement Learning	10
Airports	20	Deep Learning	26	Trajectories	13
Algorithm	15	Forecasting	33	Unmanned Aerial Vehicles (UAV)	13
Antennas	15	Learning Algorithms	21		

Source: Elaborated by the authors.

We used VOSviewer to generate a keyword occurrence map, as shown in Fig. 10, which revealed the presence of four distinct literature clusters, each representing different themes within our sample. The primary cluster (depicted in orange) encompasses ten keywords, including "air navigation," "deep learning," and "UAV." Conversely, the least populated cluster (depicted in yellow) consists of only three keywords: "airports," "big data," and "data mining." For a comprehensive overview of the keywords and their associated cluster themes, please refer to Table 3. In VOSviewer, the significance of a keyword is determined based on either its occurrence count or the total link strength (TLS). The TLS indicates the cumulative strength of the co-occurrence links between a specific keyword and other keywords (Van Eck and Waltman 2020).

The map displayed in Figs. 10 and 11 illustrates the relationship between keywords, with the size of each node indicating its weight based on the number of occurrences (larger nodes represent higher occurrences). The links between keywords indicate the network connections that a particular keyword can establish, with thicker links indicating a higher Term Frequency-Inverse Document Frequency (TF-IDF) score. One surprising finding from this keyword co-occurrence analysis is that the keyword "airlines" does not appear among the top 29 selected keywords. However, by lowering the minimum threshold for keyword occurrence to 7, the keyword "airlines" and many other keywords (81 in total) reappear, expanding the number of clusters to 7 (refer to Fig. 11).



Source: Elaborated by the authors.

Figure 10. Keyword co-occurrence map for minimum occurrence threshold = 10.

Table 3. Keywords in each literature cluster with a general theme.

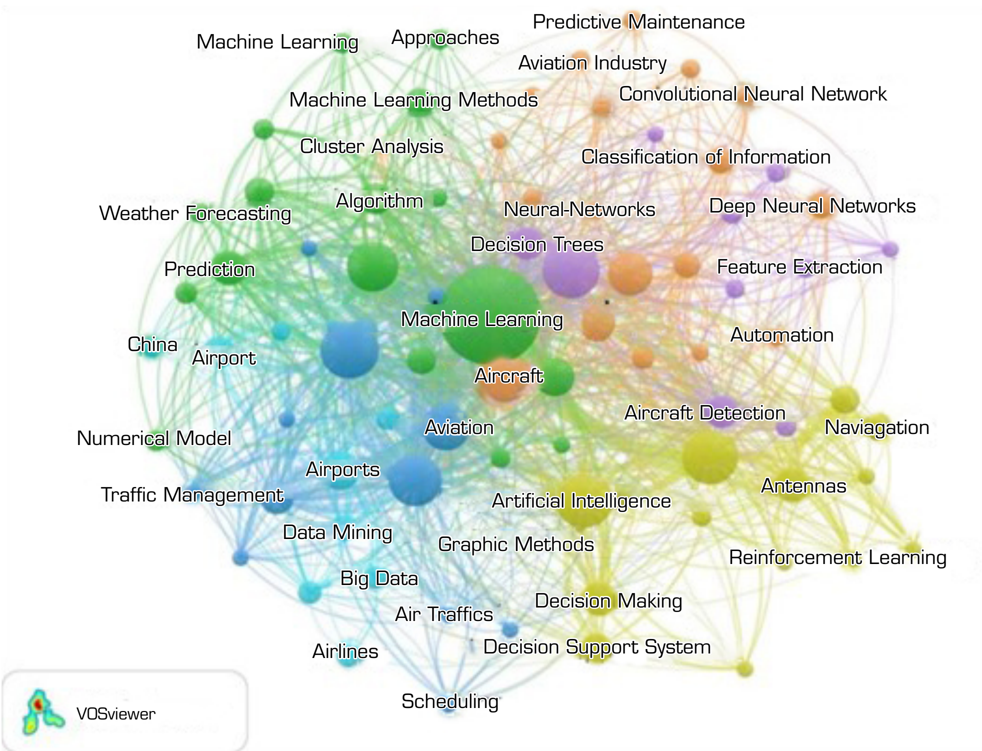
Cluster – Colour	Keyword	General Theme
Cluster 1 – Orange	Air Navigation	Machine learning algorithms applied to air navigation
	Aircraft Accidents	
	Aircraft Detection	
	Antennas	
	Deep Learning	
	Learning Algorithms	
	Learning Systems	
	Neural Networks	
	Reinforcement Learning	
	Unmanned Aerial Vehicles (UAV)	
Cluster 2 – Green	Air Transportation	Predictive analytics and ML applied to trajectory planning
	Algorithm	
	Decision Trees	
	Forecasting	
	Machine Learning	
	Machine Learning Methods	
	Prediction	
	Predictive Analytics	
	Trajectories	

Continuation...

Table 3. Continuation.

Cluster – Colour	Keyword	General Theme
Cluster 3 – Blue	Air Traffic Control	AI supporting decision making in Air Traffic Control (ATC) and Air Traffic Management (ATM)
	Air Traffic Management	
	Aircraft	
	Artificial Intelligence	
	Aviation	
	Decision Making	
	Decision Support Systems	
Cluster 4 – Yellow	Airport	Big data technologies applied to airports
	Airports	
	Big Data	
	Data Mining	

Source: Elaborated by the authors.



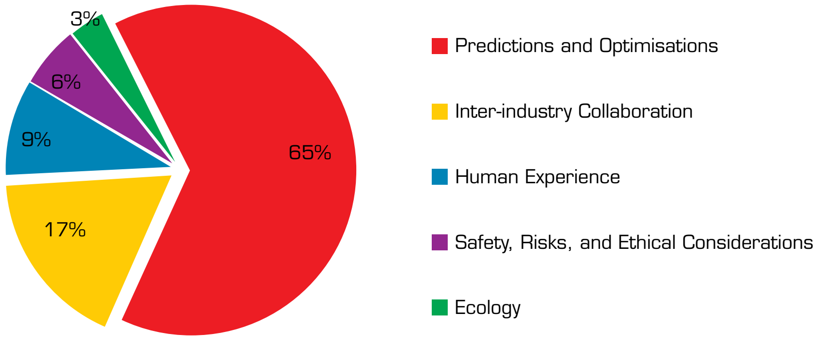
Source: Elaborated by the authors.

Figure 11. Keyword co-occurrence map for minimum occurrence threshold = 7.

FINDINGS AND DISCUSSION

By analysing the selected sample of studies, we have expanded the previously defined clusters and identified five overarching clusters that encompass the literature in this field. The first cluster, labelled “predictions and optimisations,” includes articles that offer predictive approaches to aviation problems or provide support for resolving optimisation problems using various intelligent algorithms. While it can be argued that these two categories of problems are not inherently integrated within air transport and are more focused on mathematical resolutions, it is important to note that the studies in our final sample specifically address problems relevant to the aviation industry. Therefore, these articles cover solutions that are fundamentally related to the challenges faced by the aviation industry, making them highly relevant to the field.

The second cluster revolves around the human experience, focusing on understanding best practices, techniques, and algorithms that can enhance the overall experience of individuals interacting with various services related to air transport. The ecological cluster, on the other hand, sheds light on the ongoing research direction aimed at developing eco-friendly solutions and assessing the environmental impact of new techniques in the field. Another cluster explores inter-industry collaborations, where studies may not have been directly targeted at aviation but offer techniques that can be applied to the aviation context. The selection criteria for these studies involved checking the inclusion of air transport-related keywords and conducting a thorough reading of the articles. The final cluster encompasses discussions on ethics, sustainability, responsibility, safety, and risk factors associated with AI applications in aviation. Figure 12 provides a visual representation of the percentage distribution of each cluster based on the total number of studies covering its respective theme.



Source: Elaborated by the authors.

Figure 12. Distribution of studies per cluster.

Cluster 1: predictions and optimisations

This cluster contains the largest number of studies, comprising 65% of the total. Several of these studies address the topic of delay prediction (Etani 2019; Schultz and Reitmann 2018; Wang *et al.* 2018), employing algorithms from various types, including supervised, unsupervised, artificial neural networks (ANN), and reinforcement learning. However, a critical argument can be made: the results of these studies primarily focus on optimising algorithm parameters for improved future predictions, without sufficient consideration for real-life applicability, as confirmed by our findings. Nevertheless, we also encountered studies that offered actionable insights and collaborated with airports and airline companies to effectively tackle the issue of delays.

Within this cluster, another topic explored is the prediction of the impact of natural phenomena such as wind shear, fog, or icing on aircraft operations (Huang *et al.* 2019; Larraondo *et al.* 2018; Li *et al.* 2020). The solutions proposed in these studies predominantly involve supervised learning and regression algorithms. Despite the frequent occurrence of these natural phenomena and our extensive knowledge of their effects on aircraft, the proposed solutions only offer marginal improvements (Li *et al.* 2020; Sim *et al.* 2018).

In addition, literature within this cluster covers a closely related area focused on optimising aircraft functions. This includes upgrading navigation systems for trajectory tuning (Álvarez de Toledo *et al.* 2017; Celis *et al.* 2020; Gallego *et al.* 2019), regulating fuel consumption (Malatesta *et al.* 2021; Matuszczak *et al.* 2021; Zhu and Li 2021), and suggesting intelligent diagnostic tools for monitoring the health status of aircraft (Basora *et al.* 2021; Huang *et al.* 2022; Meister *et al.* 2021). The results of these studies show promise, but their successful implementation would require the support and collaboration of aircraft manufacturers.

The subsets of air transport, namely airports, airlines, and air traffic management (ATM), have all been the focus of numerous studies exploring operations optimisation through intelligent decision-support systems based on machine learning algorithms (Midtfjord *et al.* 2022; Reitmann and Schultz 2022; Xiong *et al.* 2022). Within the domain of airports, research primarily revolves around estimating and improving the efficiency of various units (Szaruga and Załoga 2022) and employing intelligent scheduling methods for both aircraft and passengers (Bruno *et al.* 2019). For airlines, the majority of studies are dedicated to developing decision-support systems that utilize intelligent scheduling (Evler *et al.* 2021) and to optimising seat pricing (Alauddin and Ting 2020; Wozny 2022).

In the realm of Air Traffic Management (ATM), there are varying opinions regarding the integration of AI into ATM operations. For instance, Jenab and Pineau (2018) propose a neural network approach to automate ATM processes and handle increased air traffic, although their proposition is yet to be implemented. On the other hand, some researchers perceive extensive AI involvement as a risk to air operations and suggest the introduction of certification criteria to approve the use of intelligent agents in such critical positions (Kistan *et al.* 2018).

One notable aspect across these studies related to airports, airlines, and ATM is the empirical support they have received, with some of the suggested techniques already being implemented in practice.

Cluster 2: human experience

The human experience cluster comprises 9% of the selected sample, with the majority of studies focused on analysing airline customer satisfaction. These studies utilise machine learning algorithms and extract data from various sources, including customer surveys (Park *et al.* 2022), airline website reviews (Kwon *et al.* 2021; Ullah *et al.* 2021; Verma and Davis 2021), and sentiment analysis of customer tweets and social media activity (Kumar and Zymbler 2019; Rustam *et al.* 2020; Samah *et al.* 2022). While these studies employ different technical methods, they share a common theme of leveraging machine learning algorithms to tap into customers' big data.

The remaining studies within this cluster cover a range of topics. For example, Chen *et al.* (2022) examine purchase willingness, while Miskolczi *et al.* (2021) explore the attractiveness levels of airports that adopt modern technologies. Azzolina *et al.* (2021) delve into the issue of price discrimination, studying how airline companies utilise customer data for discriminatory pricing and assessing the impact of such practices on social welfare.

Cluster 3: ecology and sustainable development

In our analysis of the sample, the theme of ecology and sustainable development appears to be the least explored, with a total of eight studies found in this cluster, accounting for only 3%. Within this cluster, two articles (Tian *et al.*, 2019; Wan *et al.*, 2022) delve into the topic of aircraft gas emissions. These studies propose the utilisation of supervised machine learning algorithms to enhance situational awareness and operational efficiency by accurately estimating flight emissions and airport air quality. While it can be argued that these studies do not directly contribute to improving the global ecological state, as they focus on estimation rather than mitigation, their significance lies in initiating a dialogue on this topic, considering the limited quantity of research available. In contrast, one study (Kosir *et al.* 2020) directly addresses the issue by introducing an artificial neural network (ANN) to optimise volume swell in aviation fuel, aiming to minimise greenhouse gas emissions. Although the results of this study show promise, further replication is necessary to solidify the feasibility of its approach.

Three studies (Altringer *et al.* 2021; Dziak *et al.* 2022; Zhou *et al.* 2021) have addressed the issue of wildlife preservation within this cluster. These studies primarily aim to mitigate aviation accidents caused by animal interference, also known as wildlife strikes. Additionally, they explore the use of unmanned aerial vehicles (UAVs) to monitor various animal species in their natural habitats, utilising advanced classification algorithms to effectively identify them. Another article in this cluster focuses on beach litter monitoring, employing the same classification methods mentioned earlier. This study demonstrates improved results compared to traditional visual-census approaches (Martin *et al.* 2018).

Cluster 4: inter-industry collaborations

The cluster that ranks as the second largest, accounting for 17% of the studies, exhibits a significant degree of diversity. Within this cluster, numerous studies emerge from collaborations involving robotics, satellite imaging, and image processing, offering innovative techniques for intelligent navigation that can be applied to UAV control (Arrouch *et al.* 2022; Cai *et al.* 2021; Castagno and Atkins 2018). Another study, originating from the joint efforts of researchers from agricultural backgrounds and technologists, expands on the navigation theme. It introduces the implementation of a novel 3D filter for autonomous UAV navigation in agricultural settings, which would aid in gathering data about crop morphology (Donati *et al.* 2022).

A separate set of studies primarily focused on airport security, encompassing both physical and cyber aspects, such as the detection of suspicious behaviour, dangerous luggage, and airport x-ray scanners. In some of these studies, artificial neural networks were employed for identifying suspicious behaviour (Kim *et al.* 2020), while others utilised support vector machine-based classifiers for luggage classification (Wang *et al.* 2020). Additionally, certain works took a broader perspective, serving as meta-studies that discussed various facets of AI-based airport security (Jupe and Keatley 2020) or examined the cybersecurity threats posed by the proliferation of new intelligent systems (Koroniotis *et al.* 2020).

Furthermore, two studies based on review articles have explored the intersection of 6G, Aviation 4.0, and the Internet of Everything (IoE), providing insights into the challenges that researchers will encounter when implementing such solutions, particularly in the field of wireless communication (Janbi *et al.* 2020; Sekera and Novák 2021). In contrast, only one study emerged from the collaboration between healthcare and aviation, examining the use of drones to support medical applications such as tele-diagnostics and vaccine delivery. Although this article presents opportunities for discussion, it falls short in adequately addressing the limitations associated with such a collaboration.

Cluster 5: safety, risks, and ethical considerations

Among the research clusters we examined, this particular group has the second lowest population, accounting for just 6% of the articles in our sample. Several studies within this cluster focus on the impact of external interference on the functioning of machine learning algorithms, raising concerns about safety and the potential for severe consequences (Shaikh *et al.* 2019; Swinney and Woods 2021).

Our findings indicate that only a small portion of articles examine the ethical aspects of integrating AI in the aviation industry. For example, Igonin *et al.* (2021) delve into the concept of situational awareness regarding UAV behaviour control. Although their research primarily focuses on the technical aspects of the issue, there is still a discussion about the ethical considerations involved. Another instance is the study by Chen *et al.* (2021), which proposes the implementation of 5G-IoT monitoring devices, processed with machine learning algorithms, to establish the integrity of airport passengers by detecting potential dangerous traits or behaviours. While this study shows promise in terms of enhancing safety and minimising risks, it neglects to address any ethical dilemmas associated with monitoring human activities. Additionally, Baomar and Bentley (2021) present an impressive concept of an intelligent autopilot system based on ANN that can replicate even the most complex manoeuvres. However, their work overlooks any safety or ethical implications that may arise from such a system.

DISCUSSION

The application of AI in the air transport industry holds immense potential for enhancing efficiency, safety, and the overall customer experience. Nevertheless, it is crucial to acknowledge that the integration of AI into this industry is currently at a nascent stage, necessitating further research to comprehensively grasp its potential impact.

Despite delving into a wide range of topics and reviewing numerous high-quality papers, a noticeable bias towards predictive analysis and optimisation-focused research is evident concerning AI applications in the air transport industry. It is crucial to recognise that AI is a disruptive technology, and merely praising its technological marvels without addressing potential risks to human life, dignity, and ethical considerations would be naïve. One crucial aspect that demands further exploration is the ethical and legal implications of AI in the air transport sector. As the use of AI continues to grow in this industry, concerns regarding privacy and data protection have also become pertinent.

Further research is needed to explore the integration of AI into the current air transport infrastructure. This calls for increased collaboration between AI experts and stakeholders in the air transport industry, along with meticulous planning and seamless integration processes. An additional aspect that warrants deeper investigation is the influence of AI on employment within the air transport industry. The potential automation of numerous tasks currently undertaken by human workers due to AI advancements can result in job losses and necessitate changes in the skillsets demanded by air transport occupations. Understanding the ramifications of AI on employment in the air transport sector is crucial, and it is essential to formulate strategies that provide support to workers as the industry undergoes transformation.

Given the current state of global warming, which has significant impacts on global fauna and flora (Dai 2011), it becomes imperative to leverage advanced technological tools to promote environmental conservation and enhance resource efficiency within processes. Surprisingly, the analysis conducted in this study highlights a notable dearth of research in this specific domain. Rather than viewing air transport as a mere lock and AI as its key, our work recognises that AI serves as a transformative enabler, necessitating an interdisciplinary approach. Thus, there is still an opportunity to address this research gap through the emergence of interdisciplinary studies that aim to harness the power of AI in addressing complex problems while remaining mindful of other interconnected aspects.

CONCLUSION

The potential benefits of artificial intelligence, such as enhanced efficiency, streamlined operations, and optimised actions, are already evident across various sub-industries within air transport. Leveraging the advancements in AI, big data technologies, and machine learning algorithms as enabling technologies, this study relied on existing literature to explore the application of these technological tools in different aspects of air transport. Through a comprehensive analysis of the literature using systematic and bibliometric approaches, we gained insights into the academic discourse and evaluated the extent to which the value of AI applications has been recognised.

The findings of this study indicate that the discussions surrounding the applications of AI in the air transport industry are primarily focused on solving predictive and optimisation problems, while other areas, such as ecology and sustainability, are still in the early stages of exploration. Moreover, the research on safety, risks, and ethical considerations forms a small but gradually expanding cluster of studies that is yet to reach maturity. Conversely, there is a notable emergence of research endeavours aiming to bridge the gap between different industries by proposing adaptable solutions that can be applied to air transport, encompassing collaborations ranging from medicine to agriculture. These findings serve as a starting point for future research, providing valuable insights into the gaps present in the current literature concerning the intersection of AI and air transport.

Despite our diligent efforts to incorporate a wide range of robust studies, the focus on exclusively peer-reviewed and open-access articles introduces certain limitations. To overcome these limitations, future research could consider expanding the scope to include non-academic publications and paid publications, thus broadening the range of information sources. Additionally, further support for the explored research areas can be obtained through empirical studies, which would provide precise insights into the application of AI in various subsets of the aviation industry. Lastly, relying solely on the Scopus database as the source of documents may pose another limitation, as it is possible that some relevant works may have been overlooked in our review, even though Scopus is considered a comprehensive scholarly repository.

CONFLICT OF INTEREST

Nothing to declare.

AUTHOR CONTRIBUTIONS

Conceptualization: Eric TN and Abderrahmane MS; **Data curation:** Abderrahmane MS; **Formal analysis:** Abderrahmane MS and Eric TN; **Research:** Abderrahmane MS; **Methodology:** Abderrahmane MS; **Software:** Abderrahmane MS; **Supervision:**

Eric TN; **Validation:** Abderrahmane MS and Eric TN; **Visualization:** Abderrahmane MS; **Writing - Preparation of original draft:** Abderrahmane MS and Eric TN; **Writing - Proofreading and editing:** Abderrahmane MS and Eric TN.

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